



Evaluating the cross-efficiency of information sharing in supply chains

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ABSTRACT

Supply chain management integrates the intra- and inter-corporate processes as a whole system. Through information technology, companies can efficiently manage the product flow and information related to the issues such as production capacity, customer demand and inventory at lower costs. Information sharing can significantly improve the performance of the supply chain, how the different combination of information sharing affects the performance is not yet understood. This study designs different information-sharing scenarios to analyze the supply chain performance through a simulation model. Since there are not only desirable measures but also undesirable measures in supply chains, the usual data envelopment analysis (DEA) model allows measuring performance for complete weight flexibility. In this paper, a cross-efficiency DEA approach is applied to solve this problem. We identify the most efficient scenario and estimate the each efficiency of information-sharing scenarios. Contrary to the previous findings in the literature suggesting sharing as much as information possible to increase benefits, the results of this study show that the scenario of demand information sharing is the most efficient one. In addition, sharing information on capacity and demand, and full information sharing in general are good practices. Sharing only information on capacity and/or inventory information, without sharing information on demand, interferes with production at manufacturers, and causes misunderstandings, which can magnify the bullwhip effect.

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1. Introduction

A supply chain is a logistics network, which consists of all stages (e.g. order processing, purchasing, inventory control, manufacturing, and distribution) involved in producing and delivering a final product or service. The entire chain connects customers, retailers, distributors, manufacturers and/or suppliers, beginning with the creation of raw material or component parts by suppliers and ending with consumption of the product by customers. Supply chain management (SCM) is related to the coordination of materials, products and information flows among suppliers, manufacturers, distributors, retailers and customers (Simchi-Levi, Kaminsky, & Simchi-Levi, 2000). SCM often needs the integration of inter- and intra-organizational relationships and coordination of different types of flows within the entire chain. With sharing information between trading partners and coordinating their replenishment and production decisions under demand uncertainty, it could be possible to further reduce costs and improve customer service level. The performance of a supply chain could be influenced by

many factors, among which information sharing is the crucial one. Inter-company integration and coordination via information technology play a key role in improving supply chain performance. The application of current information technology, such as electronic data interchange (EDI) and the internet has helped companies to share information and has improved supply chain order fulfillment performance. Sharing both supply and demand information substantially reduces inventory costs in make-to-stock or assemble-to-order production. Sharing supply information also substantially reduced order cycle time in an assemble-to-order environment (Strader, Lin, & Shaw, 1999).

A supply chain is fully coordinated when all decisions are aligned to approach global system objectives. Lack of coordination occurs when decision makers have incomplete information or incentives that are not compatible with system-wide objectives. Even under conditions of full information availability, the performance of the supply chain can be sub-optimal when each decision maker optimizes one's individual objective (Sahin & Robinson, 2002). One line of related research analyzes the benefits of sharing customer demand information with members of the supply chain. Bourland, Powell, and Pyke (1996) analyze the savings in inventory cost that can be realized when a manufacturer shares point-of-sale (POS) data with suppliers. Ernst and Kamrad (1997) consider a supply chain in which manufacturers and retailers share demand information and analyze the impact of information sharing on

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service level. Lee, Padmanabhan, and Whang (1997) prove that demand variability can be amplified in the supply chain as the orders are passed from retailers to distributors. Therefore, accurate forecasts can significantly influence the performance of the supply chain in terms of inventory cost, backorders or loss of sales, and good will. Inaccurate forecasts can also cause low utilization of capacity and other problems in production. Cachon and Fisher (2000) and Lee et al. (2000) analyze the benefits of sharing real-time information on demand and/or inventory levels between suppliers and customers. Cachon and Fisher (2000) study the value of sharing demand and inventory data. The authors compare a traditional information policy that does not use information-sharing with a full information policy. Lee, So, and Tang (2000) analyze the benefits of demand-side information sharing with a two-echelon supply chain. They suggest that this kind of information sharing alone could provide significant inventory reduction and cost savings to the manufacturer. Thonemann (2002) derives a better understanding of the benefits of advance demand information (ADI) to identify conditions under which sharing ADI results in significant cost savings. A typical model is used to capture the basic aspects of a supply chain in which ADI is shared. This enables them to derive analytical results and to gain structural insight into the ADI-sharing problem. The results can be used by decision makers to analyze the cost savings that can be achieved by ADI and help them determine if sharing ADI is beneficial for their supply chain.

Another line of related research analyzes the impact of information sharing on the bullwhip effect and/or the performance of a supply chain. Metters (1997) studies the impact of the bullwhip effect on profitability by establishing an empirical lower bound on the cost excess of the bullwhip effect. Results indicate that the importance of the bullwhip effect to a firm differs greatly between specific business environments, and eliminating the bullwhip effect can increase product profitability by 10–30% under some conditions. Chen, Drezner, Ryan, and Simchi-Levi (2000a) Chen, Ryan, and Simchi-Levi (2000b) quantify the bullwhip effect for a simple, two-echelon supply chain consisting of a single retailer and a single manufacturer. They assume that demand follows an AR(1) process, and the retailer uses a moving-average model for demand forecast and a simple order-up-to inventory policy for replenishment. They conclude that the variance of the orders is always higher than the variance in demand. Furthermore, the magnitude of the variance is significantly influenced by the number of observations used in the moving-average, the lead time between the retailer and the manufacturer, and the correlation coefficient in the demand function. They extend the analytical model to a multiple-echelon supply chain and find that the bullwhip effect could be reduced, but not completely eliminated, by sharing demand among all parties in the supply chain. Chen et al. (2000a, 2000b) investigate the impact of forecast methods and demand patterns on the bullwhip effect. They compare an exponential-smoothing forecasting model and a moving-average model, in which the demand is correlated with a linear trend. They find that reduction in ordering lead time and using more demand information in forecasting (a smoother forecast) could decrease the bullwhip effect. Another finding is that negatively correlated demand could lead to a larger increase in order variability than positively correlated demand, and that a retailer forecasting demand with a linear trend will have more variable orders than a retailer forecasting i.i.d. demand. These two papers evaluate the magnitude of the variance amplifications in the supply chain by considering alternative demand processes and forecasting models for a simple supply chain structure. However, they do not consider the impact of the variance amplifications on the costs and service levels of the supply chain, nor do they consider the costs of either inventory, ordering or setup, or production decisions by the manufacturers. Zhao, Xie, and Leung (2002a) present the impact of information sharing and ordering coordination

on the performance of a supply chain with one capacity-limited supplier and multiple retailers under demand uncertainty. Zhao, Xie, and Leung (2002b) also present the impact of forecasting model selection on the value of information sharing in a supply chain with one capacitated supplier and multiple retailers. Using a computer simulation model, this study examines demand forecasting and inventory replenishment decisions by the retailers and production decisions by the supplier under different demand patterns and capacity tightness. The simulation output indicates that the selection of the forecasting model significantly influences the performance of the supply chain and the value of information sharing. Furthermore, demand patterns faced by retailers and capacity tightness faced by the suppliers also significantly influence the value of information sharing. The results also show that substantial cost savings can be achieved through information sharing and then motivating trading partners to share information in the supply chain.

Information sharing can significantly improve the performance of a supply chain. Additionally, companies can redesign their supply chain strategies through information sharing to increase profit. Many studies demonstrate the positive impact of information sharing on a supply chain. However, few studies focus on how the different combinations of information sharing affect the performance of a supply chain. Provided that the entities of supply chain are aware about how they can benefit from the information sharing, they are more willing to share the necessary information. The purpose of this paper is to examine how the different information sharing among the entities influences the performance of the supply chain, and to address the problem of selecting the most appropriate information sharing for the supply chain partners. This study designs different information-sharing scenarios to analyze the supply chain performance. To measure the performance of each scenario, it is necessary to consider not only the desirable indices but also undesirable indices. Thus, the usual data envelopment analysis (DEA) model is applied to measure the performance for complete weight flexibility.

The remainder of the paper is organized as follows. In the next section, the information-sharing scenarios are specified. A brief introduction of cross-efficiency DEA and the analysis for evaluating performance are described in the following section. The analysis and results are demonstrated in Section 4. In the final section, some conclusions and recommendations for further research follow.

2. Information-sharing scenarios

We develop a supply chain simulation model (shown in Fig. 1) which considers a multi-echelon supply chain (i.e. retailers, distributors, manufacturers and suppliers) and nine information-sharing scenarios. In the first information-sharing scenario, denoted by N, no information will be shared between the entities. The second scenario is partial information sharing, which consists of six combinations: (1) C: capacity information sharing; (2) D: demand information sharing; (3) I: inventory information sharing; (4) D&C: demand and capacity information sharing; (5) D&I: demand and inventory information sharing; (6) C&I: capacity and inventory information sharing. The third scenario, denoted by F is full information sharing with capacity, demand and inventory. The fourth scenario is strategic alliance of supply chain (vendor managed inventory, VMI, is adopted herein).

To compare the performance of each information-sharing scenario, a simulation tool, Rockwell Software Arena v5.0, is utilized to analyze performance indices (shown in Table 3). Input parameters such as initial inventory level, inventory policy, lead times of production and transportation, customer demand rate, and unit production time are shown in Tables 1 and 2.

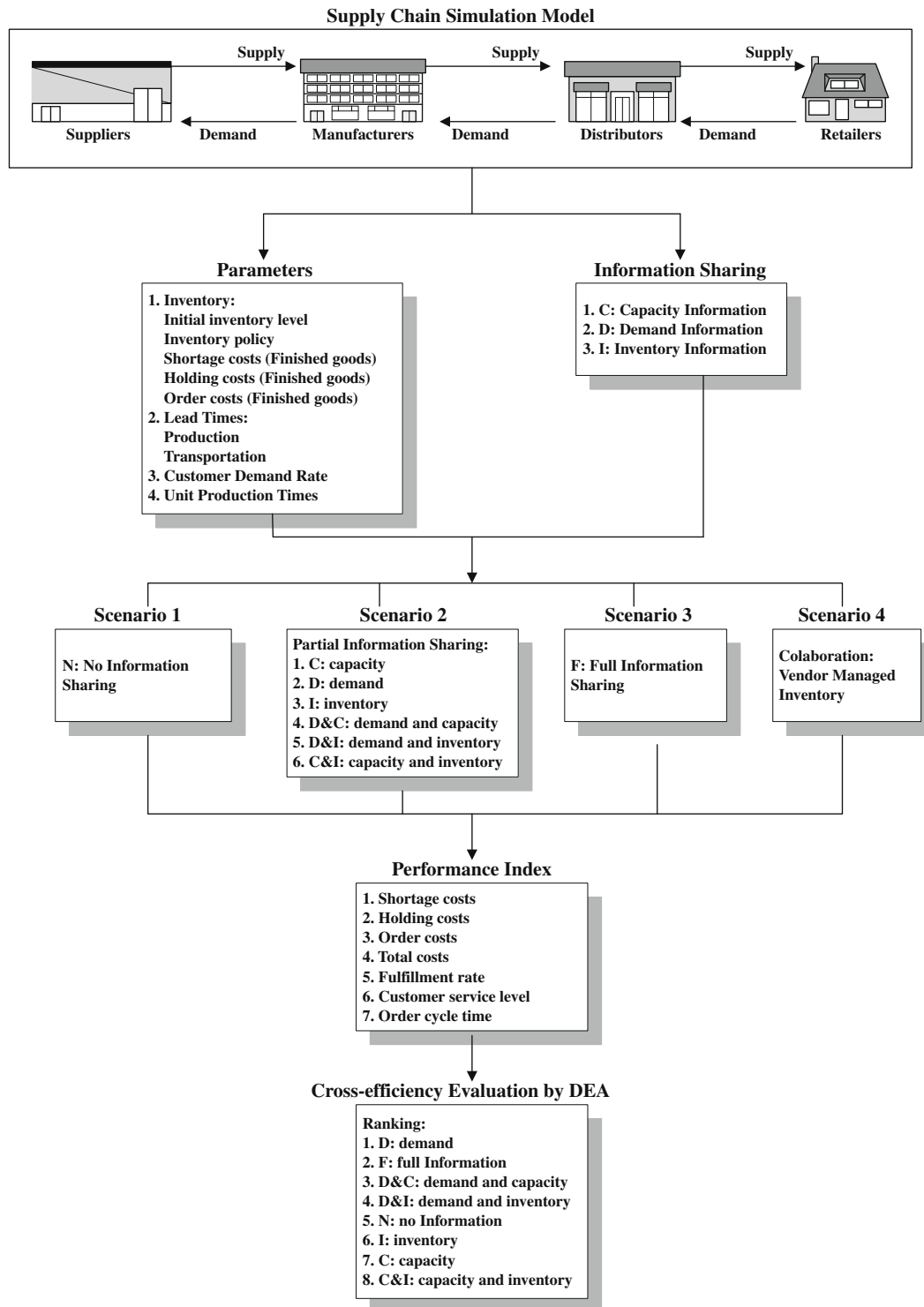


Fig. 1. Supply chain simulation model.

The above simulation results of performance indices include total costs (consisting of inventory holding cost, shortage cost and order cost), fulfillment rate, customer service level and order cycle time. From the performance measures of each scenario illustrated in Table 3, we cannot easily determine the most appropriate scenario with respect to the performance data of these eight information-sharing scenarios, except for the scenario of VMI, since each performance measure is relatively prominent. This can be seen as a problem of discrete alternative multiple criteria evaluation, which is formulated by considering a set of alternatives and a set

of criteria. The aggregation and comparison of various alternatives are based on the values for each criterion. In most approaches, the multi-criteria evaluation for an alternative is represented by a vector of the performance of the alternative on each criterion. This information is then used within the outranking methods to carry out relative rankings and performance evaluations among the values of the alternatives for a given criteria.

Salminen, Hokkanen, and Lahdelma (1998) compare a number of models and tools based on outranking approaches for multiple criteria decision making (MCDM) and a multi-attribute rating

Table 1
Initial inventory level and inventory policy.

Inventory	Retailer 1	Retailer 2	Retailer 3	Distributor	Manufacturer
Initial inventory level	40	40	40	130	200
Inventory policy (s, S): s	21	24	21	61	83
Inventory policy (s, S): S	39	43	39	129	153

Table 2
Parameters for simulation.

Parameters	Inputs
Iteration	30
Simulation time	120 days
Interval distribution of customer order	Exponential distribution (mean = 0.15 day)
Quantity distribution of customer order	Discrete distribution (Q = 1 or 4, Prob. = 0.167; Q = 2 or 3, Prob. = 0.333)
Frequency of replenishment review	Once daily
Transportation lead times	1 (day)
Production lead times	Normal distribution (mean = 0.1 h, standard deviation = 0.02 h)
Unit holding costs	1
Unit shortage costs	5
Order costs	10 (retailers), 50 (distributors and manufacturers)

technique. The outranking techniques were applied with a number of actual decision makers (DMs) providing preference weights for each of the major criteria. The outranking approaches typically require three sets of inputs: preference weights for the criteria, preference and indifference thresholds and veto thresholds. The usual approach would be to have the DM provide information relative to the preference weights and some information on veto thresholds levels. The determination of this information for large groups may be cumbersome. The DEA models require little input from the DM. Doyle (1995) has supported the use of the DEA as a lazy DM's methodology for MCDM. This outlook may alternatively be looked at as a reactive approach to MCDM. That is, the DMs, or their preferences, play an insignificant role in the ranking of alternatives. Meanwhile those usual MCDM weighting methods to aggregate different criteria into one performance index are more subjective, thus DEA methodology is utilized to measure cross-efficiency between different information-sharing scenarios.

3. Methodology

This paper presents an atypical application of data envelopment analysis (DEA) methodology to measure performance of coordination and information sharing between the supply chain entities at different information sharing scenarios. The DEA method, first proposed by Charnes, Cooper, and Rhodes (1978), is known as an evaluation technique for performance analysis of various entities whose production activities are characterized by multiple inputs

and outputs. A reader can see more details of the DEA method in Boussofiene, Dyson, and Thanassoulis (1991), Charnes, Cooper, and Lewin (1994), Seiford and Thrall (1990). Nowadays, DEA has become one of the most popular fields in operations research, with applications involving a wide range of contexts. The applicability and practicality of DEA can be easily confirmed in Cooper, Huang, and Li (1996), Cooper, Thompson, and Thrall (1996) and numerous previous research efforts. The DEA method is utilized to analyze the performance with multiple inputs and outputs. Thus, we apply this method to evaluate SC information sharing performance. In the supply chain, each unit is permitted to choose the most favorable weights to be applied to its standings (in our case, the different information-sharing scenarios are compared by analyzing the resulting performance measures including total cost, order fulfill rate, customer service level and order cycle time) in the usual DEA manner. In the evaluation of this simple efficiency score, the usual DEA model allows for complete weight flexibility. A unit achieves a relative efficiency score of 1 by heavily weighting few favorable inputs and outputs, and completely ignoring the other inputs and outputs. Such units perform well with respect to few input/output measures. Thus, considering the scenarios with an efficiency score of 1 as the candidates with the best combination of specifications is inappropriate. Cook and Kress (1990) consider a scheme involving an imposed set of weights, which do not provide a fair overall assessment. Nevertheless, the problem of choosing the most favorable weights to be applied to each unit's standings is still not resolved. The simple efficiency score obtained from Cook and Kress's model is often misleading. To overcome such problems, a measure more than the simple efficiency score is required in the decision making process. In this section, we provide a review of basic DEA and a cross-efficiency ranking extension to the DEA models and how they may be used to help evaluate discrete alternative MCDM models.

Traditionally, one method for resolving this problem is for the poll organizer to impose a predetermined set of weights on each alternative's standing. Thus the composite score, Z_i , of alternative i would be given by:

$$Z_i = \sum_{j=1}^k w_j v_{ij} \quad (1)$$

where v_{ij} represents the value of j th attribute of alternative i ($i = 1, 2, \dots, m, j = 1, 2, \dots, k$), and w_j denotes the weight of the j th attribute.

The CCR model was initially proposed by Charnes et al. (1978). For each DMU, the CCR model tries to determine the optimal

Table 3
Simulation results of performance indices.

Scenario	N	C	D	I	D&C	D&I	C&I	F	VMI
Shortage costs	219.78	66.15	29.44	109.84	26.088	54.05	95.80	24.79	–
Holding costs	103.06	293.63	233.36	189.94	401.25	262.12	371.13	479.88	–
Order cost	130	180	130	130	180	130	180	180	–
Total costs	452.84	539.78	392.8	429.77	607.34	446.17	646.94	684.68	241.08
Fulfillment rate (%)	65.22	75.25	79.26	72.16	79.13	77.04	72.36	79.35	98.50
Customer service level (%)	61.83	72.62	77.44	68.84	77.26	74.66	76.42	81.30	98.09
Order cycle time (days)	1.3593	1.1205	1.0568	1.1961	1.0475	1.0943	1.1762	1.0451	1.0021

weight of j th attribute of alternative i , w_{ij} , using linear programming so as to maximize the composite score Z_{ii} which are used in the objection function (2) to emphasize that this is alternative i 's own evaluation of its own desirability.

$$\text{Maximize } Z_{ii} = \sum_{j=1}^k w_{ij} v_{ij} \tag{2}$$

$$\text{Subject to } Z_{ip} = \sum_{j=1}^k w_{ij} v_{pj} \leq 1 \text{ for all DMUs } p, \text{ including } i \tag{3}$$

$$w_{ij} \geq 0 \tag{4}$$

where Z_{ip} denotes cross-efficiency of alternative i 's evaluation of alternative p 's desirability i.e. DMU p is evaluated by the weights of DMU i . Constraints (3) represent that no alternative p should have a desirability greater than 1 under i 's weights.

The optimal weights may vary from one DMU to another. Thus, the weights in DEA are derived from the data instead of being fixed in advance, such as given by decision makers. Each DMU is assigned a best set of weights with values that may vary from one DMU to another. Cook and Kress (1990) suggest that each alternative be allowed to propose its own weights in order to maximize its own desirability subject to certain reasonable constraints on the desirability of all the alternatives. Sexton, Silkman, and Hogan (1986) argue that decision makers do not always have a reasonable mechanism from which to choose assurance regions. Thus they recommend the cross-evaluation matrix (CEM) for ranking alternatives. Cross-efficiencies in DEA can effectively be used to surmount the problems associated with simple efficiency scores. Cross-efficiencies of a DMU provide information on how well it is performing with the optimal DEA weights of other $m - 1$ DMUs. The cross-efficiencies of all the DMUs can be arranged in a CEM as shown in Table 4. The p th row and i th column of the CEM represents the cross-efficiency of DMU p with the optimal weights of DMU i . The usual simple efficiency measurements for each DMU are found in the leading diagonal of this matrix. The cross-efficiency method simply calculates the efficiency score of each DMU m times using the optimal weights evaluated by m LPs. The cross-efficiency ranking method in the DEA context utilizes the results of cross-efficiency matrix Z_{ip} in order to rank scale the DMUs. It could be argued that $\bar{Z}_i = \sum_{p=1}^m Z_{pi}/m$ is more representative than Z_{ii} , the standard DEA efficiency score, since all the elements of the cross-efficiency matrix are considered, including the diagonal. While the standard DEA score, Z_{ii} , is non-comparable, since each uses different weights, the \bar{Z}_i is comparable because it uses the weights of all units equally (i.e. all the units' standing).

A limitation with the CEM evaluated from Sexton et al. (1986) model weights is that the optimal weights obtained from their model may not be unique. This condition occurs if multiple optimum solutions exist. This ambiguity can be solved by using formulations proposed by Doyle and Green (1994). These formulations can be categorized into aggressive and benevolent approaches, in which Doyle and Green (1994) not only maximize the efficiency

of target DMU, but also take a second goal into account. The second goal, in the case of aggressive formation, is to minimize the efficiency of the composite DMU constructed from other $m - 1$ DMUs. The aggressive formulation is shown below:

$$\text{Minimize } \sum_{j=1}^k \left(w_{ij} \sum_{p=1, p \neq i}^m v_{pj} \right) \tag{5}$$

$$\text{Subject to } Z_{ip} \leq 1 \text{ for all DMUs } i \neq p \tag{6}$$

$$\sum_{j=1}^k w_{ij} \cdot v_{ij} - Z_{ii} = 0 \tag{7}$$

$$w_{ij} \geq 0 \tag{8}$$

where DMU i is the target DMU, $\sum_{j=1}^k (w_{ij} \sum_{p=1, p \neq i}^m v_{pj})$ is the weighted attributes of composite DMU, and Z_{ii} is the simple efficiency of DMU i obtained from usual DEA.

Maximizing the other DMUs' cross-efficiencies in the same way is known as a benevolent formulation:

$$\text{Maximize } \sum_{j=1}^k \left(w_{ij} \sum_{p=1, p \neq i}^m v_{pj} \right) \tag{9}$$

$$\text{Subject to } Z_{ip} \leq 1 \text{ for all DMUs } i \neq p \tag{10}$$

$$\sum_{j=1}^k w_{ij} \cdot v_{ij} - Z_{ii} = 0 \tag{11}$$

$$w_{ij} \geq 0 \tag{12}$$

When aggressive models (5)–(8) are solved for alternative i , as well as obtaining Z_{ii} , we are also provided with values Z_{ip} which can be thought of as evaluations of p 's desirability from i 's point of view within this modeling framework. The values obtained in a complete run of the model can be organized in a matrix Z in which the values down a column p ($Z_{\bullet p}$) represent how alternative p is appraised by all alternatives, and values across a row i ($Z_{i \bullet}$) represent how alternative i appraises all alternatives. Thus, this matrix can be regarded as the summary of a self- and peer-appraisal process in which on-diagonal elements represent self-appraisals, and off-diagonal elements represent peer-appraisals.

Sexton et al. (1986) propose the column averages of Z as suitable overall ratings of the alternatives. In essence, each alternative is being accorded a weight of $1/m$ in determining any alternative's overall rating. In order to mitigate the rank reversal effect, Green, Doyle, and Cook (1996) relax the assumption that each alternative be accorded a weight of $1/m$ in the establishment of overall ratings. They suggest that each alternative apply a weight in proportion to its original overall rating rather than uniformly $1/m$.

4. Results and discussions

The data for this study are shown in Table 3. A total of 8 scenarios and six criteria (performance measures) are introduced. The six performance measures include three minimizing criteria (holding

Table 4
Matrix of cross-efficiencies for m DMUs.

Rating DMU	Rated DMU					
	1	2	3	...	m	Averaged appraisal of peer
1	Z_{11}	Z_{12}	Z_{13}	...	Z_{1m}	\bar{B}_1
2	Z_{21}	Z_{22}	Z_{23}	...	Z_{2m}	\bar{B}_2
3	Z_{31}	Z_{32}	Z_{33}	...	Z_{3m}	\bar{B}_3
⋮	⋮	⋮	⋮	⋮	⋮	⋮
m	Z_{m1}	Z_{m2}	Z_{m3}	...	Z_{mm}	\bar{B}_m
Averaged peer-appraisal	\bar{Z}_1	\bar{Z}_2	\bar{Z}_3	...	\bar{Z}_m	

cost, shortage cost, order cost and order cycle time). The remaining criteria (fulfillment rate, customer service level) are defined as the maximizing criteria. There are many studies which consider treating minimizing criteria. We begin with a brief summary of these recent works related to the treatment of minimizing criteria into four categories. First are some studies which regard them as following weak disposability, such as Färe, Grosskopf, Lovell, and Pasurka (1989), Boyd and McClelland (1999), Zofio and Prieto (2001). Weak disposability indicates that the undesirable outputs can be reduced only at the expense of a reduction in the other outputs or an increase in the use of inputs. The second possibility is to envision them as inputs, such as Haynes, Ratick, and Cummings-Saxton (1994) and Korhonen and Luptacik (2004). This method considers both inputs and undesirable outputs (minimizing criteria) to have the same improvable direction when inefficient DMUs wish to improve their performance, and then, undesirable outputs are treated as inputs. Thirdly, some studies treat them as desirable outputs by taking their reciprocal, such as Lovell, Pastor, and Turner (1995), and the fourth group treats them by subtracting them from some sufficiently large numbers, such as Seiford and Zhu (2002), Jahan-shahloo, Hadi Vencheh, Foroughi, and Kazemi Matin (2004). The translated data in the third and fourth categories have the same improvable direction with desirable output, and then the efficiency scores will be obtained by employing a traditional DEA model. In our study, we treat those minimizing criteria as desirable outputs by taking their reciprocal, since there is no production relationship between minimizing criteria and maximizing criteria.

Models (2)–(4) are initially used to obtain the simple efficiency of all SCM information-sharing scenarios. The standard DEA identified scenarios N, D, I, D&I, and F to be efficient with a relative efficiency score of 1. The remaining 3 scenarios (C, D&C and C&I) obtained an efficiency score of less than 1. No specific argument is advanced for preferring an aggressive over a benevolent approach. However, since the major interest is in finding the best SCM information sharing rather than a group of projects to make up a program, an aggressive approach, in the eye of some neutral evaluator, may be seen as appropriate in this context. Thus, simple efficiency scores are then used in aggressive models (5)–(8) to obtain the optimal attribute weights for each scenario. These weights also minimize the relative efficiency of the composite scenarios that is constructed from the remaining $m - 1$ scenarios for each case. Such a matrix and overall rating is shown in Table 5. It is evident from this table that scenarios D and F have several high cross-efficiency values. Some of the simple efficient scenarios such as N and I have several low cross-efficiency values. The adjusted weighted column means of the Z matrix can be used to effectively differentiate among the overall efficient scenarios.

Scenario D&C, which was inefficient with a relative efficiency score of 0.999 and mean score of 0.819, is rated as a better overall performer than efficient scenarios N, D&I and I, and as almost equal

to scenario F. Based on these results, the optimal choice is scenario D – a good overall alternative performing well in many dimensions. This methodology allows the decision maker to rank the SCM information-sharing scenarios based on their overall performance.

Demand information has a tendency to amplify, delay and oscillate from downstream to upstream along the supply chain (Forrester, 1998; Lee et al., 2000). This information is fundamental and important to supply chain partnership. Furthermore, demand information has a major impact on supply chain performance since it has a direct impact on production scheduling, inventory control and delivery plans (Thonemann, 2002). Therefore, sharing demand information is usually taken as the first step for supply chain partnership. For example, more than 50% of manufacturers in the personal computer industry share their demand information with suppliers (Austin, Lee, & Kopczak, 1997). From our results shown in Table 5, the scenarios with sharing demand information outperform the other scenarios.

The results also show that the no information-sharing scenario (N) is better than some partial information-sharing scenarios (C, I, C&I). This seems most unreasonable, but is an interesting and meaningful result. According to the simulation, sharing only capacity and/or inventory information, without any demand information sharing, causes interference with production at manufacturers and misunderstandings, and magnifies the bullwhip effect. The business activities are triggered by demand. The activities, such as production in the upstream of the supply chain, try to meet the actual demand of end customers. Better meeting of actual demand results in better consequent decisions in the supply chain. Therefore, sharing only capacity and/or inventory information, without any demand information sharing, may mislead the sales forecast, inventory control and production plan.

5. Concluding remarks and further research

After proceeding with international management, enterprises have to face the challenge of SCM mainly because of the rapid change in the business environment and severe competition in market and customers' diverse demand. Therefore, how to operate information technology to upgrade the efficiency of a supply chain has currently become one of the most important issues for enterprises. Information sharing is usually taken as a basic treatment for supply chain collaboration. In a supply chain, more direct and immediate information results in higher accuracy of forecasts. The effective SCM is not achievable by any single enterprise, but instead requires a virtual entity by faithfully integrating all involved partners, who should come up with the insightful commitment of real-time information sharing and collaborative management. Thus assessing the effects of different degrees of information

Table 5
Cross-efficiency and overall rating for 8 SCM information sharing scenarios.

	N	C	D	I	D&C	D&I	C&I	F
N	1.000	0.351	0.442	0.543	0.257	0.393	0.278	0.215
C	0.826	0.949	1.000	0.911	0.996	0.971	0.912	1.000
D	0.483	0.557	1.000	0.563	0.965	0.728	0.474	1.000
I	1.000	0.722	1.000	1.000	0.722	1.000	0.722	0.722
D&C	0.810	0.940	1.000	0.891	0.999	0.965	0.893	1.000
D&I	1.000	0.722	1.000	1.000	0.722	1.000	0.722	0.722
C&I	0.929	0.925	1.000	0.919	0.961	0.958	0.955	1.000
F	0.113	0.375	0.842	0.226	0.950	0.459	0.259	1.000
Overall rating	0.759	0.674	0.914	0.742	0.819	0.800	0.631	0.830
Ranking	5	7	1	6	3	4	8	2

Note: N: non-information sharing, C: capacity information sharing, D: demand information sharing, I: inventory information sharing, D&C: capacity and demand information sharing, D&I: demand and inventory information sharing, C&I: capacity and inventory information sharing, F: full information sharing.

sharing upon multi-echelon supply chain performance has become an important issue.

Differing information-sharing scenarios are compared by analyzing the resulting performance measures including: inventory holding costs, shortage costs and order costs of manufacturers, order filling rates of distributors and retailers, customer service levels, and order cycle time. The ranking of scenarios according to performance measures is often treated in the literature as the problem of multi-criteria classification of elements of one set. Besides the application of multi-criteria analysis, this problem has been solved by applying different methods such as regression analysis, cluster methods, and factor analysis. This study aims at using a non-parametric approach, DEA, to estimate the efficiency of information-sharing scenarios in a supply chain with multiple criteria.

Most applications of DEA to multi-criteria analysis have the limitations of the existing methodology intrinsic to DEA. The simple efficiency score obtained from standard DEA is often misleading. It is difficult to choose the best alternative. In order to rank 5 efficient alternatives we use an aggressive formulation of Doyle and Green's DEA cross-efficiency model (Doyle and Green, 1997). A comparison of obtained ranks shows that the scenarios were ranked more realistically with the cross-efficiency matrix. The results show that the scenario of demand information sharing is the most efficient. Besides, the sharing of information on capacity and demand, and full information sharing in general, are good practices.

The previous findings in the literature suggesting sharing as much as information possible to increase benefits, we contrarily advise to share the information as combination. This research can be extended in several ways. Firstly, different types of inventory policy can be applied to comparing the efficiency of information sharing. Secondly, since the results of the simulation show that the demand information is the key enabler for information sharing, the demand information, including the interval and quantity distribution of customer orders, can be changed to test the sensitivity of parameters. Third, the preference of each managerial factor can be further considered, and how the preferences derived from different managerial factors can be further examined in future works.

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